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In an ever-increasing interest for Machine Learning (ML) and a favorable data development context, we here propose an original methodology for data-based prediction of two-dimensional physical fields. Polynomial Chaos Expansion (PCE), widely used in the Uncertainty Quantification community (UQ), has long been employed as a robust representation for probabilistic input-to-output mapping. It has been recently tested in a pure ML context, and shown to be as powerful as classical ML techniques for point-wise prediction. Some advantages are inherent to the method, such as its explicitness and adaptability to small training sets, in addition to the associated probabilistic framework. Simultaneously, Dimensionality Reduction (DR) techniques are increasingly used for pattern recognition and data compression and have gained interest due to improved data quality. In this study, the interest of Proper Orthogonal Decomposition (POD) for the construction of a statistical predictive model is demonstrated. Both POD and PCE have amply proved their worth in their respective frameworks. The goal of the present paper was to combine them for a field-measurement-based forecasting. The described steps are also useful to analyze the data. Some challenging issues encountered when using multidimensional field measurements are addressed, for example when dealing with few data. The POD-PCE coupling methodology is presented, with particular focus on input data characteristics and training-set choice. A simple methodology for evaluating the importance of each physical parameter is proposed for the PCE model and extended to the POD-PCE coupling.

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## 1. Introduction

Deep Learning techniques (DL [1]) and more generally Machine Learning (ML [2]), and their applications to physical problems (fluid mechanics [3]; plasma physics [4]; quantum mechanics [5], etc.) have made a promising take-off in the last few years. This has been particularly the case for fields where the measurement potential has dramatic Geoscience Data [6]). In this context, learning techniques are of interest to establish non-linear physical